EXPERIMENTAL MODAL ANALYSIS AND DAMAGE DETECTION IN A SIMULATED THREE STORY BUILDING

Tim R. Fasel[1], Seth W. Gregg[2], Tim J. Johnson[3], Chuck Farrar[4], Hoon Sohn[4]

[1]Case Western Reserve University, undergraduate aerospace engineering
[2]Colorado State University, undergraduate mechanical engineering
[3]Purdue University, graduate mechanical engineering
[4]Staff Member, Los Alamos National Laboratory, Los Alamos, New Mexico 87545

ABSTRACT: This paper is a continuation of a study entitled "Damage Detection in Building Joints by Statistical Analysis" [1] in which accelerometer data were acquired from a simulated three-story building driven by an electro-dynamic shaker attached to the base of the structure. Joint damage and environmental conditions were simulated and data were collected systematically for comparison. Operational variability was introduced by changing the shaker input amplitudes and frequency range. An Auto-Regressive model with Exogenous Inputs (ARX) was fit to the collected data and the standard deviations of the residual errors between ARX predictions and the measured data were used as the damage sensitive features. A Sequential Probability Ratio Test (SPRT) was used to make damage detection decisions. The test produced promising results, but was shown to be sensitive to the operational and environmental variability. This investigation was conducted as part of a conceptual study to demonstrate the feasibility of detecting damage in structural joints caused by seismic excitation.

NOMENCLATURE:

x = acceleration time history value
α = auto-regressive (AR) model coefficients
α,β = ARX model coefficients
e = AR residual error
ε = ARX residual error
n = number of data points
μ = mean
σ = standard deviation
Z_n = SPRT test statistic
a,b = upper and lower bounds of Z_n, respectively

1. INTRODUCTION

Recent earthquakes have shown that welded moment-resisting steel connections are susceptible to failure [2]. Current methods of damage detection for joints in buildings subjected to earthquakes are quite costly and time-consuming visual procedures. If a damage detection method based on measured vibration response can be developed, it can then be combined with current MEMS or fiber optic sensing technology, constituting a more economical and quantifiable damage detection method. Such a damage identification method can potentially provide significant economic and life-safety benefits. The focus of this study is to conceptually demonstrate a vibration-based damage detection system for structural connections.

In the research presented herein, baseline data sets measured from a structure in an undamaged state were compared in a statistical manner to data sets measured from the structure after various damage conditions had been introduced to the structural connections. The test structure was representative of a three-story frame building. A modal analysis of the structure preceded the damage detection portion of the experiment to lend insight into the dynamic response of the structure. The damage detection method used in this study was composed of a four-part process [3,4]:

1. Operational evaluation,
2. Data acquisition and cleansing,
3. Feature extraction, and
4. Feature discrimination through statistical modeling.

Possibly the most important part of implementing a damage detection strategy is to determine the appropriate damage-sensitive features to be extracted from the data. Features that are highly sensitive to damage while being insensitive to other variables must be chosen. The features extracted are used to develop a statistical model, which will discriminate between features from the undamaged and damaged states.

2. TEST STRUCTURE DESCRIPTION

The test structure (shown in Figure 1) was a simulated three-story frame structure, constructed of Unistrut columns and aluminum floor plates. Floors were 0.5-in-thick (1.3-cm-thick) aluminum plates with two-bolt connections to brackets on the Unistrut columns. Floor heights were adjustable. The base was a 1.5-in-thick (3.8-cm-thick) aluminum plate. Support brackets for the columns were bolted to this plate. All bolted connections were tightened to a torque of 220 inch-pounds

(25Nm) in the undamaged state. Four Firestone airmount isolators, which allowed the structure to move freely in horizontal directions, were bolted to the bottom of the base plate. The isolators were mounted on aluminum blocks and plywood so that the base of the structure was level with the shaker. The isolators were inflated to 10 psig (69 kPag). The shaker was connected to the structure by a 6-in-long (15-cm-long), 0.375-in-dia (9.5-mm-dia) stinger connected to a tapped hole at the mid-height of the base plate. The shaker was attached 3.75-in from the corner on the 24-in (61-cm) side of the structure, so that both translational and torsional motion would be excited.

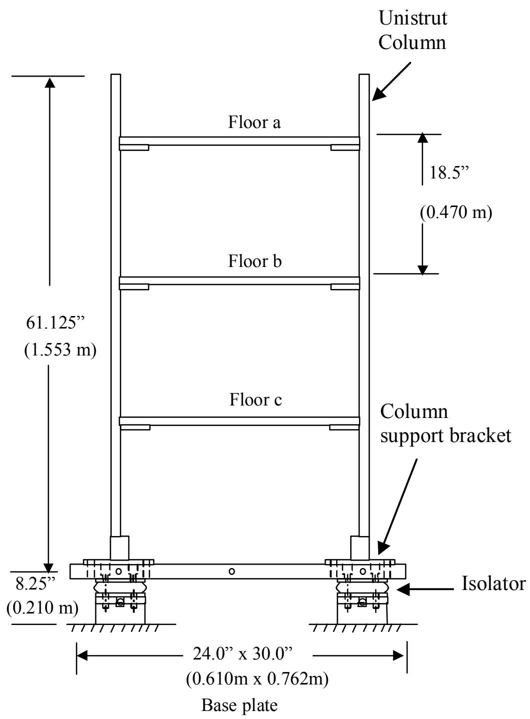

Figure 1. Assembled frame structure, out of plane shaking (not to scale).

3. MODAL ANALYSIS

The benefits of performing modal analysis on the structure were threefold. First, the modal testing acted as a thorough system check. Faulty accelerometers or wires were replaced and a general familiarity with the data acquisition system was gained during these tests. The second benefit was the insight on operational variability gained by performing two separate modal tests. The structure was taken apart between the tests then reassembled and tested a second time. These two tests allowed us to examine how the structure's modal frequencies were affected by slight structural changes. A summary of the modal frequencies is given in Table 1. The third reason for the modal analysis was to gather data with which to correlate a finite element model being developed outside this experiment. Accelerometer triads were placed at each joint for the modal analysis. Figure 2 shows a sample mode shape.

Table 1: Modal Analysis Results.

Frequency (Hz)		Mode (X and Y direction)
Test 1	**Test 2**	
2.288	2.309	Rigid body Y
3.037	3.109	Rigid Body X
12.568	12.71	1st Torsion
13.903	14.396	1st Bending X
14.457		1st Bending Y
24.87	24.726	2nd Torsion
32.038	31.749	Possible Unistrut Mode
40.081	39.087	2nd Bending X
49.816	49.297	Possible Unistrut Mode
69.095	66.034	2nd Bending Y
73.424	69.633	3rd Torsion
74.297	71.626	3rd Bending X
120.327	114.651	3rd Bending Y
138.887	134.714	4th Torsion
145.037	144.645	Possible Air Bearing Mode
187.593	184.17	Possible Floor Plate Mode

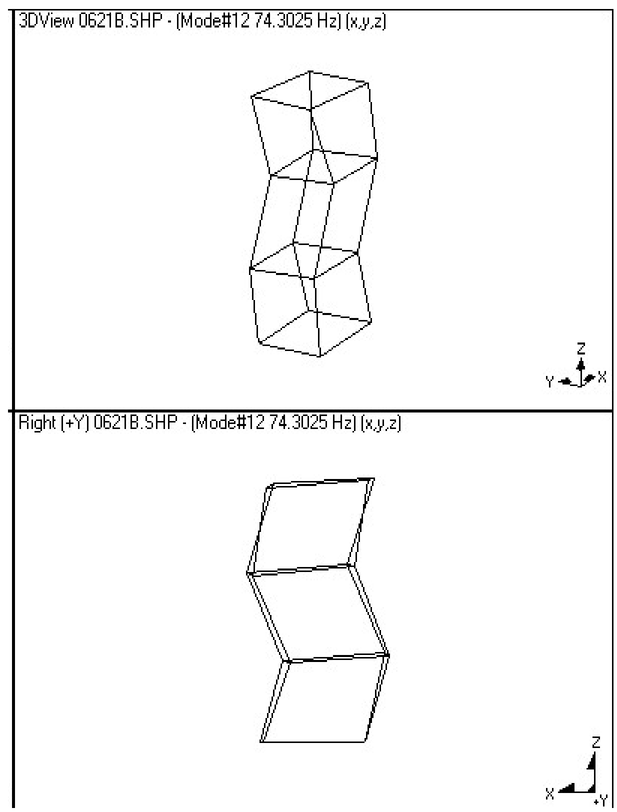

Figure 2: 12th mode of the test structure.

4. OPERATIONAL EVALUATION

Operational evaluation is essentially the problem definition phase; this involves defining the scope of the experiment [5]. In this stage, damage was defined and implementation flexibility and variability of the structure were considered. Damage definition should attempt to model the effect of damage in actual structures. Damage was defined as a significant change in dynamic response of the structure. This was evaluated with the SPRT described in section 7. Implementation flexibility governs the number, placement, and type of sensing devices to be used in the test. For this test, sensor pairs were placed at each joint. If the method used in the experiment is overly complicated or costly it will be impractical to implement. Variability was introduced in three forms: environmental, operational and testing variability. Each of these sources of variability must be carefully considered and the feature extracted for damage detection should be insensitive to all of them.

5. DATA ACQUISITION AND CLEANSING

The structure was instrumented with 33 piezoelectric accelerometers, two per joint (see Figure 3) plus additional pairs at damage joints. Accelerometers were mounted on blocks glued to the floors and Unistrut columns. This configuration allowed relative motion between the column and the floor to be detected. The nominal sensitivity of each accelerometer was 1 V/g. Additionally, a force transducer was mounted between the stinger and the base plate. This force transducer was used to measure the input to the base of the structure. A commercial data acquisition system controlled from a laptop PC was used to digitize the accelerometer and force transducer analog signals.

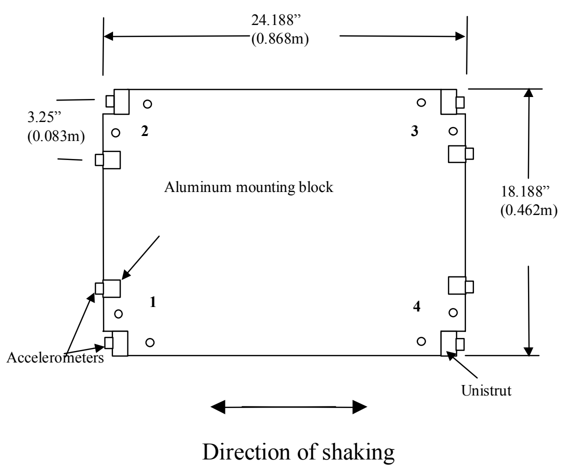

Figure 3: A typical floor plan showing sensor locations.

The sensor and cabling setup was verified by sending a low frequency sine wave into the structure and visually inspecting the read-outs for each channel. The acceleration time histories were analyzed in the feature extraction and statistical modeling portion of the study. For this type of measurement, 8-second time histories were sampled at a rate of 512 samples/sec. A uniform window was applied to these measurements.

A matrix of baseline undamaged data sets was recorded before damage was introduced to the structure. This included operational and environmental variability from varying the shaker input level, adding mass to the structure, and placing a small handheld shaker outputting a 100 Hz sine wave on the building. Before acquiring each data set, the pressure in the air mounts was inspected, the bolt torques throughout the structure were verified and the accelerometers were also inspected for proper mounting. Damage was introduced by loosening or removing bolts at the joints as summarized in Table 2.

Table 2: Test Cases.

Damage Case 1	No clamped mass, joint 2a has induced damage
Damage Case 2	Clamped mass on level a, joint 4b has induced damage
Damage Case 3	Clamped mass on level b, joints 4b and 2a have induced damage
Damage Case 4	Clamped mass on level c, induced damage at joint 4b, loose masses on level a and level b
Damage Case 5	Clamped mass on levels a & b, induced damage at joints 2a and 4b, handheld shaker emitting sign wave on level a

The time histories for the paired accelerometers at each joint were numerically subtracted, giving the relative acceleration at each joint. The relative signals were normalized by subtracting their respective mean values and dividing by their standard deviations. This data normalization process was used to minimize any shifts caused by DC offsets and to minimize shaker amplitude dependence. Hereafter the normalized relative signals will be referred to as the data signals.

6. FEATURE EXTRACTION

Because of the accelerometer placement, the relative difference between adjacent column and plate acceleration time histories should demonstrate movement at the joint. If the plate is securely bolted to the bracket, both accelerometers should provide similar readings. If damage is introduced at a joint, the adjacent accelerometers should exhibit some quantifiable difference in their readings. For this reason the difference between the time histories measured from accelerometers on the column and on the plate at every joint was examined. An AR model was first fit to each data signal. Residual errors between actual time history differences and predicted differences were computed. These residual errors were used as the approximated inputs to the ARX models. Because the AR-ARX model is a linear predictive model, it was assumed that residual errors from this model applied to a nonlinear, or damaged, case would be larger and exhibit greater variance than when the linear model was applied to the intact, linear structure. Also, it was assumed that the largest changes in the residual errors would be associated with the damaged joint. Thus the standard deviation of the residual errors from the AR-ARX model was used as the selected damage detection feature.

The AR model used in this study was:

$$x(t)=\sum_{i=1}^{40}\alpha_i x(t-i)+e(t) \qquad (1)$$

Where 40 is the model order, α's are coefficients that weigh previous response measurements, x, and e is the residual error term. The order of the AR model was determined using a partial auto-correlation function [6]. Successive AR models of increasing order are fit to the data and the magnitudes of the last alpha coefficients from these various models are plotted. The point at which the alpha values fall below a specified tolerance is selected as the order of the AR model. For this study the tolerance was set at $1/\sqrt{n}$. Figure 4 shows a plot of the partial auto-correlation function. Based on this analysis an AR model of order 40 was chosen. Figure 5 shows a comparison of the 40th order model and a 100th order model with the actual data; the 40th order model was sufficient.

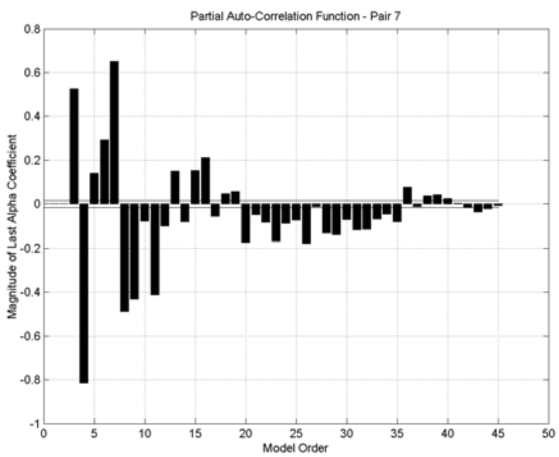

Figure 4: Partial auto-correlation of an undamaged test case.

This model is then fit to the data signals at each joint and alpha coefficients are derived by a least squares fit. The residual errors are calculated from the AR model and are used as approximated input to the ARX model given here:

$$x(t)=\sum_{i=1}^{8}\alpha_i x(t-i)+\sum_{j=0}^{7}\beta_j e(t-j)+\varepsilon(t) \qquad (2)$$

Where α and β are the linear predictor coefficients and ε is the residual error (α here is different from the α in the AR model). For the undamaged cases α and β were determined by a least squares fit and saved in an array. The damaged cases were then paired with the undamaged cases experiencing the same operating conditions. This pairing was done both through a least squares matching of the AR coefficients and manually. The damaged (test) data were then fit to AR-ARX models using the coefficients from the undamaged cases.

The model order of the AR-ARX was determined by looking at the AR-ARX residual errors and determining when they were small enough [6]. An order of 8 sufficed here.

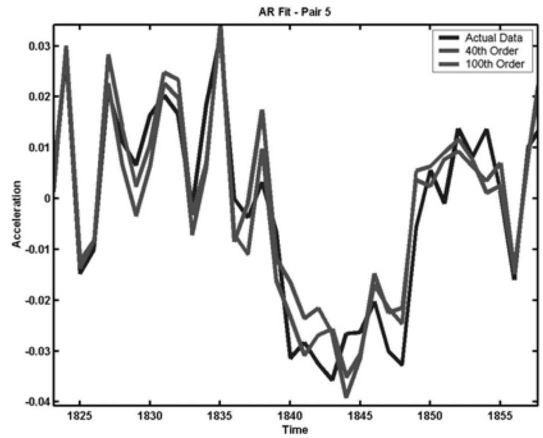

Figure 5: Comparison of actual data with 40th and 100th order fit AR models.

7. STATISTICAL MODELING

A Sequential Probability Ratio Test was used to establish when a significant change in the damage-sensitive feature had occurred [7,8]. The residual errors of the AR-ARX model fit to the data signals when the structure is in good condition will have some distribution with mean, μ, and standard deviation, σ. If the structure is damaged, then the mean, the variance, or both might change. Statistical process control provides a framework for monitoring future residual error values and for identifying new data that are inconsistent with past data.

Here the decision is whether or not the system is damaged. The standard deviation is used to make a decision, and we develop two hypotheses.

$$H_0: \sigma \le \sigma_0 \text{ and } H_1: \sigma \ge \sigma_1$$

Where σ_0 and σ_1 are experimentally determined values of standard deviation that represent thresholds of undamaged and damaged σ's respectively. We develop a test statistic:

$$Z_n=\sum_{i=1}^{n}\frac{1}{2}\left(\frac{1}{\sigma_0^2}-\frac{1}{\sigma_1^2}\right)(\varepsilon_i-\mu)^2-\ln\left(\frac{\sigma_1}{\sigma_0}\right) \qquad (3)$$

This Z_n is then tracked as more data come in and damage is indicated when a Z_n exceeds the "undamaged" region as seen in Figure 6. Here the Z_n diverges rapidly for the data signals at the damaged joints and a clear decision can be made. The undamaged region is defined heuristically by a and b, which are the upper and lower limits, respectively. However, because of the nature of the method, initial incorrect guesses can be made, as in Figure 7; these are usually corrected by delaying a decision until sufficient amounts of data are recorded. Sometimes no clear decision can be made even after much data have been collected. Figure 8 shows a case where all the data signals are muddled. There is no clear distinction between the damaged and undamaged joints. This data came from a test case with a large amount of environmental variability.

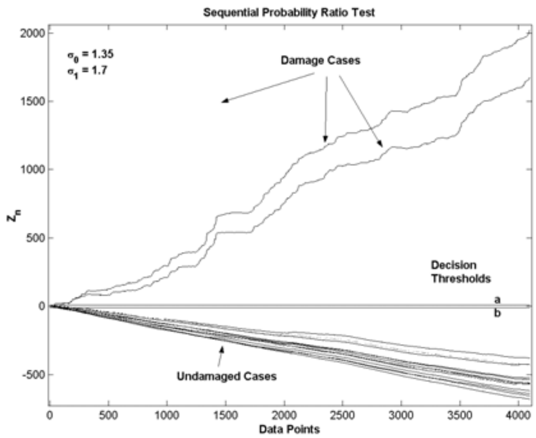

Figure 6: Z_n plot used in SPRT; all the data signals from the building are plotted. The ones corresponding to damaged joints diverge rapidly.

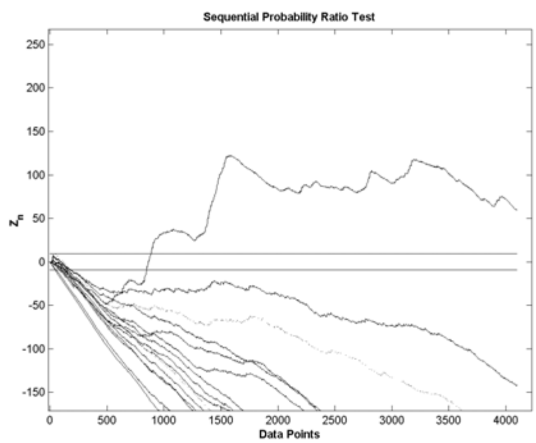

Figure 7: SPRT makes an initial wrong decision.

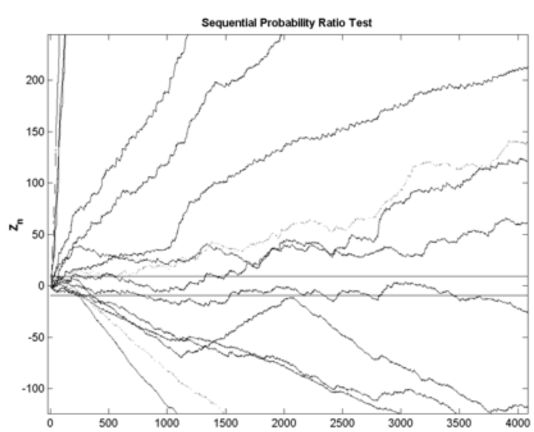

Figure 8: Decision is difficult to make in ambiguous case.

8. CONCLUSIONS AND FUTURE WORK

Accelerometer Location:
Sensors detecting relative vertical (z-direction) motions could have a practical placement advantage because they are less dependent on whether excitation at the structure's base takes place in the x or y direction. The accelerometers at these locations were surprisingly sensitive to damage, yet susceptible to false positive decisions. Future work should definitely include a more detailed look as to whether the relative vertical motion would be a choice for joint damage detection.

In general, the sensors in line with the excitation (x-direction) were most effective while sensors lined up perpendicular to excitation (y-direction) were wholly ineffective.

Excitation Levels:
As expected, the level of excitation played a large role in the detection effectiveness. At the highest excitation levels, the damage detection process worked relatively well; as excitation levels were lowered, this detection ability was severely reduced. At the low excitation levels, the relative background noise was much higher and the results were much more sporadic. A systematic way of choosing σ_0 and σ_1 could improve the detection effectiveness at the mid-range (and more practical) levels of excitation.

Environmental Conditions:
The ability to detect damage with imposed variability in the environmental conditions depended on the excitation level and the condition imposed. The addition of loose masses had little effect at high excitation levels, while the hand shaker seemed to have devastating effects on the detection ability in general. With improved values of σ_0 and σ_1, damage detection with loose masses at mid level excitation should be attainable.

SPRT and Feature Choice:

The standard deviation of the AR-ARX errors appeared to be quite sensitive to damage. A more appropriate method for choosing σ_0 and σ_1 should be developed to obtain optimum detection abilities. The Sequential Probability Ratio Test worked reasonably well at reducing the amount of data needed to produce a correct decision. From Figure 8 one can see a few data signals diverging extremely quickly at the start of the plot; these correspond to damaged joints. However, the algorithm is not able to correctly discern them as the only damaged joints, as is obvious from the many other data signals diverging above the threshold. A visual inspection can determine the damaged joints but no numerical method yet developed works here.

This study was undertaken to conceptually demonstrate a vibration-based damage detection system for structural connections in building subject to earthquakes. With the cost of current data acquisition technology it would be considered prohibitively expense to put two accelerometers at every joint in an in-situ steel frame structure. However, current developments in MEMS sensing technology (see www.imimems.com) coupled with recent developments in wireless data acquisition and transmission systems [9] indicate that instrumenting every joint in a structure will be economically feasible in the near future. The results of this study show that there is the potential to identify and locate the damage at a joint if such an instrumentation system were put in place.

9. ACKNOWLEDGEMENTS

Funding for the Los Alamos Dynamics Summer School was provided by the Engineering Science and Applications Division at the Los Alamos National Laboratory and the Dept. of Energy's Education Programs Office. The following companies provided data acquisition hardware and various software packages that were necessary to complete the student projects: Dactron, Inc. (data acquisition hardware), Vibrant Technologies (experimental modal analysis software), The Mathworks, Inc. (numerical analysis software), and ANSYS, Inc. (finite element software).

10. REFERENCES

1. Allen, Castillo, et al., "Damage Detection in Building Joints by Statistical Analysis." Proc. 19th International Modal Analysis Conference. Orlando, FL, 2000.
2. "Steel Moment Frames After Northridge: Special Issue of the J. of Structural Eng.," David Darwin, Edt.,126, No. 1, 2000
3. Farrar, C. R. and S. Doebling, "The State of the Art in Vibration-Based Structural Damage Identification, A Short Course." Los Alamos Dynamics, Ltd. 2000.
4. Farrar, Doebling, et al. "Vibration-Based Damage Detection" in Structural Dynamics @ 2000: Current Status and Future Directions. Ed. D.J. Ewins and D.J. Inman. Baldock, Hertforshire, England: Research Studies Press Ltd, 2001.
5. Farrar, Doebling, et al. "Vibration-Based Structural Damage Detection." Phil. Trans. R. Soc. Lond. A 2001: 131-149.
6. Sohn, H, C. R. Farrar, N. F. Hunter and K. Worden "Applying the LANL Statistical Pattern Recognition Paradigm for Structural Health Monitoring to Data from a Surface-Effect Fast Patrol Boat," Los Alamos National Laboratory report LA-13761-MS, 2000.
7. Montgomery, D. C., Introduction to Statistical Quality Control, John Wiley & Sons, Inc., New York, 1996.
8. Ljung, Lennart. System Identification: Theory for the User. 2nd ed. NJ: Prentice Hall PTR, 1999.
9. Straser, E. "A Modular, Wireless Damage Monitoring System for Structures," Doctoral Dissertation, Civil Engineering Dept., Stanford University, 1998.